Spatial Capture-Recapture IV: Modifying the state-space

OUTLINE

- Discrete state-space
  - Wolverine example (not analyzed here)
  - Experiments with the Fort Drum data set
- Density covariates
- Likelihood estimation

PART IV: USING A DISCRETE STATE-SPACE

- Our previous models have used a continuous state-space and specified independent uniform priors for each coordinate of the activity center variable, s[i]

- Often we have state-space restrictions that are important. E.g., wolverine camera trapping study.

- Can’t use the uniform prior for s[i] in these cases

  - Certain polygon constraints can be solved analytically (e.g., triangular state-spaces, or maybe piecewise linear).

- In such cases, we can impose those constraints by using a discrete approximation to the state-space as a mesh of points.

Prior distribution for s

- With a discrete state space uniformity is expressed like this

    s.id[i] ~ categorical(probs[1:ngrid])

    probs[g] = 1/ngrid

- Instead of:

s[i] ~ Uniform(S)

FORT DRUM BLACK BEARS

- Let’s reanalyze the Fort Drum data using a discrete states-space

REANALYSIS OF THE FORT DRUM DATA WITH A DISCRETE STATE-SPACE

- R work session

DENSITY COVARIATES

- So far we have assumed activity centers are distributed uniformly over the landscape.

- What if we have a covariate defined for every pixel of the landscape and we think individuals should favor choosing home range location based on that?

Prior distribution for s

- With a discrete state space uniformity is expressed like this

  s.id[i] ~ categorical(probs[1:ngrid])

  probs[g] = 1/ngrid

- **But there is no need to retain the uniformity assumption!**
- If you have a covariate then do this:

  probs[g] = exp(beta*Cov[g])/[$\sum_g \exp(beta * Cov[g])$]

- If beta = 0 then reduces to uniform probabilities.

SUMMARY